Analysis on the Impact of Network Platform Recommender Systems on Users' Choices of Network Music

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Abstract
In the technological era, we always come across recommender systems. The passage mainly focuses on the use of recommender system in the music field, and analyzes the positive and negative aspect of the system and its future applications. The statistics of the paper are mainly from the former researches. It turns out that the recommender systems have both positive and negative influence on the musical industry. Recommendation systems benefit niche singers a lot, for the reason that their songs can be spread wider and more listeners will hear their songs. From the users' perspective, they will be recommended fair-sounding songs that fit their music tastes. However, recommender systems still yield ethical challenges that waited to be solved.

Keywords-*recommender systems, recommendation systems, music, music industry*

1. INTRODUCTION

Sometimes people need to make decisions without sufficient personal experience. People always take other people's advice or recommendations to make a decision. When people use their digital devices in the daily life, they always come across with recommender (or recommendation) systems (RS). For example, services and apps like Amazon and Netflix apply recommender systems on a regular basis. To be more precisely, recommender systems speculate the users' predilection, such as a particular song or a new movie's coming out, according to a series of algotithms and functions.

The system has five dimensions in technical design space [4]. First of all, the contents of an evaluation are really flexible. Secondly, while recommendations may be entered explicitly to the users, several systems collect implicit estimates. Thirdly, recommendations can be anonymous, source-identified, or pseudonymous. The fourth dimension, and also one of areas that waits for exploration, is how to aggregate evaluations. The final aspect is that the (possibly aggregated) evaluations may be used in various ways: they can filter out negative recommendations, or evaluations can be accompanied by a display item.

Over the course of the last 20 years, RS have been developed focusing mostly on business services like iTunes and Spotify, and their emphasis are always on commercial goals. As a matter of fact, RS have a wider impact on users themselves and on society. After all, they shape users' preferences and guide their choices, on both individual and social level.

People interact with recommendation systems a lot in their daily lives. However, people do not know how recommender systems work and how they collect users' information. This leads to a sense of insecurity among users. Apparently, there is a lack of researches about the privacy problems of recommendation systems. Thus, the paper intends to focus on the music field and try to figure out what influences recommend systems have on the music field. The paper wishes to know RS better and hope more researches will be done in the future.

2. LITERATURE REVIEW

A variety of researchers have been researching the impact of the recommender systems over the decades.

There are some papers that focus on recommender systems of music industries. Chen and Markus Schedl both present the mechanism and algorithm of music recommendation system [1-2]. Kartik Hosanagaruses an empirical study of the music industry to conclude that the recommender systems are in fact helping users to create commonality with others [3].

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Unfortunately, the research is sparse in the field of addressing the ethical challenges posed by RS. provides one of the most detailed accounts. There are five areas that are ethically problemetic: data publishing, the practices of user profiling, user interface design, algorithm design and online experimentation or A/B testing [8-10].

3. RECOMMENDER SYSTEM

Recommendation systems can be divided into two broad categories: content-based recommendation (CBF) and collaborative filtering (CF) [5]. Content-based filtering is based on the characteristics of the user's preference and the item's description. In CBF method, keywords can be adopted to describe items to indicate whether users like or dislike the items. In other words, CBF algorithms recommend items to customers depending on whether those items are similar to those items that are favoured by the customers in the past.

Music recommendation problem has its unique characteristics. First of all, there is obviously a huge discrepency in consumption time between music (just a few minutes) and other domains such as books (a few days or weeks or even month) and movies (a few hours). Consequently, the time it takes for users to form their musical taste is much shorter than books and movies. Therefore, users can listen to several songs in a short time. According to this profile, the evaluation criteria and the algorithmic solutions have a large difference from the more standard techniques in the literature of Markus Schedl [2]. Additionally, music recommendation systems can abstract music elements. For instance, music recommender systems can recommend music by similar genre, album or artist.

4. THE POSITIVE IMPACT

4.1. Statistic

The Million Song Dataset Thierry Bertin-Mahieux is a collection for one million contemporary songs [4]. The following is a visualized figure describing the distribution of predicted usage patterns. It is a figure that employs potential factors predicted from audio [6].

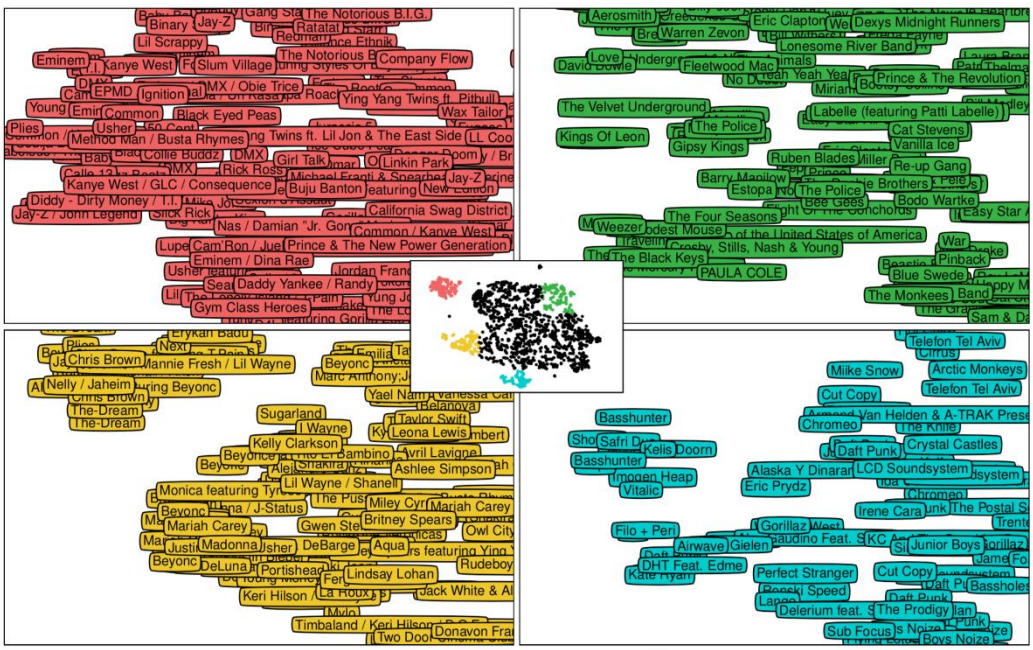

Figure 1. Visualization of the distribution of predicted usage patterns.

It can be found that Figure 1 is best viewed in color. Red represents hip-hop, green represents rock, yellow represents pop and blue represents electronic music. It can be observed that the singers with a similar style (such as pop, rap) are more likely to appeal to the same audience. Therefore, users that listen to the a specific singer might be recommended other singers that are similar to the specific singer. And then users will develop more semblable taste of music. Furthermore, the matches seem to be a little bit more varied. This is a useful discovery for recommender systems, which means that those less popular singers will have a bigger possibility to be heard from listeners.

4.2. Commonality

First of all, the value recommenders offer is called personalization, which means the consumption experience is personalized to each user's taste. Users can widen their interests through a personalization system, therefore creates commonality with others [3]. In general, user's purchase appears more similar after recommendations. There are two reasons why recommender systems help increse commonality, which are taste effects and volume effects. The taste effect is a phenomenon that more consumers purchase a similar product portifolio after recommendations. The volume

effect is that, consumers buy more goods after seeing personalized recommendations. At the individual level, close users becoming more intimate and remote users becoming more distant. Overall, consumers become more alike, and the consumer network becomes denser, more connected, and narrower.

In the music industry, the characteristics of consuming quickly means that one song may be consumed repeatedly (even multiple times in a row), while other media products are usually consumed a few times at most. This implies that a user might appreciate suggestions of already known items.

From a practitioner's point of view, it can be noted that collaborative filtering techniques are inherently domain agnostic. In music, however, explicit scoring data is relatively scarce, if available, often less than that of other fields. In contrast, implicit positive feedback often comes from uninterrupted listening events.

5. THE NEGETIVE IMPACT

The overuse of recommender systems might also lead to ethical problems. Generally, the more information RS has about a person, the more risk a person might face. Users may not want their habits to be widely known.

5.1. Ethical impact

It is clear that ethical problems need to be understood and solved properly. If not, this may result in opportunity costs and problems which could have been lessened or avoided altogether. As a result, the public will distrust and dislike the use of RS [11].

There are mainly two kinds of negative impact: one is that a recommendation may be inaccurate. This might lead to lessening utility for the user and get the relevant parties into trouble. The other is that users might take the risk of being exposed to inappropriate privacy violations by external actors, or being exposed to potentially irrelevant or damaging content.

5.2. Privacy

User privacy may be seen as unavoidable, for most of commercially successful recommender systems are based on hybrid or collaborative filtering techniques. These complicated techniques function by constructing models in order to generate personalized recommendations to their users. Clearly, this is also a vital challenge for recommender systems [10-11].

There are mainly four situations when privacy risks may occur. Firstly, when data are collected or shared secretly, without informing the users. Secondly, after collecting data, the stored data might be leaked to external agents [6]. Thirdly, even if the data are collected and stored accurately and securely, privacy concerns still exists. There is still possibility that the system can construct a profile for those consumers who have fewer data [7].

The user-centred recommendation framework also introduces explicit privacy controls, that is to let the consumers decide whether and with whom their data can be shared [9]. However, user-centred approaches can shift their responsibility and burden to the users.

6. FUTURE APPLICATIONS

The table below shows the profit of some popular websites though using recommender system [5].

Netflix	2/3rd of the movies watched are recommended
Google News	recommendations generate 38% more click-troughs
Amazon	35% sales from recommendations
Choicestream	28% of the people would buy more music if they found what they liked

Figure 2. Companies benefit from recommender systems.

It can be observed from the figure 2 that those companies gained a respectable amount of revenue from recommender systems. They use recommendation systems to generate recommendations to their customer, and then systems collect their feedbacks into database. After that, the collected data can be used for generating new recommendations through algorithm in the next user-system interactions.

In the future, it can be expected that, a variety of commercial investments will apply recommender systems in products ranging from music to movies, videos, and books. We can also expect follow-up technological innovations to deeper understand which features are best suited for the diverse characteristics of the project in the coming years.

7. CONCLUSION

The paper makes a brief overview of the impact of the use of recommendation systems on the field of music. It describes the superior characteristics of music. Recommendation, using recommendations in other domains as a comparison. Later, it focuses on the positive and negative impacts of the recommender system, and their future applications. From the positive aspect, recommendation system increases users commonality and exposes users to more niche singers. From the negative aspect, the ethical challenge of the recommender systems cannot be ignored.

Unfortunately, there is still lack of statistics about RS performance on the music fields, and it can be further illustrated the detailed influence of the recommendation systems. Besides, the ethical challenge of the recommender systems is still waited to be solved.

Hopefully, recommender systems will become more developed and more ameliorated, and more researches will be conducted about the recommender systems used on the music fields.

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